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LETTER

A model for selecting the best sustainable airport technology alternatives

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Abstract

Air transport is a continually expanding industry, a fact that has become even more evident with the recovery of the aviation industry post-COVID-19. This expansion amplified energy consumption at airports, which was already significantly high. Airport decision-makers are increasingly focusing on improving sustainability and addressing social, economic, and environmental criteria across airports worldwide. In this article, we propose a decision-making model for identifying a sustainable airport technology solution that minimizes the energy consumption of airport lighting while considering economic, emission, and life-cycle criteria. The proposed model combines data envelopment analysis and multi-criteria decision making techniques. We applied the model to the Dallas/Fort Worth International Airport (DFW) as a case study, considering eight lighting technology solutions, each with five luminous flux alternatives. Our model identified the best lighting technology solution for DFW outdoor and indoor environments based on the following criteria: luminous flux, capital costs, life-cycle costs, energy consumption, and emissions (CO_2e, NO_x, SO_2, and $PM_{2.5}$). The designed model is customizable to any airport and is applicable to a wide range of airport lighting technologies. In our analysis, Light-Emitting Diode lighting emerged as the most sustainable technology option. It ranked first in most cases due to its balance of high efficacy, long lifespan, low life-cycle cost, low capital cost, and lower emissions across all pollutants.

1. Introduction

Airports are complex infrastructure systems in need of sustainability solutions. They consist of two parts: (1) the landside infrastructure (such as terminal buildings, curbs, parking structures) and (2) airside (such as runways, taxiways, and apron areas). These infrastructure systems have been accommodating continual worldwide growth in passenger demand, which increased by 66% between 2010 and 2019 (ICAO 2019). This growth was significantly impacted by the pandemic (COVID-19), but as of January 2025, passenger traffic was 3.8% above the pre-pandemic (2019) levels (IATA 2025). The increase in air travel demand has highlighted the need to expand airport landside infrastructure, such as terminal buildings (Balliauw and Onghena 2020, Sun *et al* 2023, Varzeghani *et al* 2023), and airport parking structures, as shown by the volume of surface traffic at airports (Cheng and Qi 2019, Wadud 2020). The expansion of airport landside infrastructure has been common in countries such as the United States (U.S.), where passengers primarily use private vehicles for ground access to airports. The increase in air traffic demand has led to the construction of massive airport parking lots, underground parking facilities, and multistory parking structures that require significant energy for lighting (Mahpour *et al* 2024).

The increase in air travel demand has also led to a rise in aircraft emissions at airports. Airports utilize the greenhouse gas protocol (GHG protocol) for greenhouse gas (GHG) accounting (GHG Protocol 2001). This protocol divides airport emissions into three scopes: Scope 1 (direct emissions owned and controlled by airports), Scope 2 (indirect emissions from energy sources that airports can influence, such as purchased electricity and heat), and Scope 3 (indirect emissions that airports do not own and have limited control over, such as aircraft landing and takeoff (LTO) cycle and ground access vehicles). Although the emissions generated by aircraft during the LTO cycle produce the highest amount of emissions on airport premises, and would contribute significantly to GHG emission reduction in airport sustainability programs, these emissions are not directly controlled or managed by airports because they fall under Scope 3 emissions (ACRP 2009, ACI 2010, Greer *et al* 2020). However, airports' purchased electricity (Scope 2) for lighting implies that airports can directly influence their electricity consumption by choosing appropriate lighting. For this reason, we focus on lighting in this article, as it is one of the key technologies that airports can directly control and manage.

Since lighting is a significant contributor to the energy consumption of airport infrastructure (Ortega Alba and Manana 2016, Kim *et al* 2020), it plays a substantial role in airport operations, typically accounting for 15% of an airport's total energy costs (SMUD 2020). Lighting demand is a critical part of modern airport sustainability planning. Many major global airport hubs have implemented sustainability programs that address energy efficiency, waste flow, emissions, user experience, and other impacts that span economic, environmental, and social criteria (FRA 2023, HKG 2023, SFO 2023, SYD 2023). Additionally, many airports strive to follow the Leadership in Energy and Environmental Design (LEED) standards for their buildings, as LEED is the most widely recognized green building rating system and an international benchmark for environmental responsibility (US Green Building Council 2025).

Achieving continued success for broad goals such as sustainability is challenging. Airport managers can adopt evaluation methods to select sustainable design alternatives that overcome these challenges. Implementing sustainability requires valuing trade-offs in decision-making when assessing alternatives across sustainability criteria. This is most evident when evaluating the environmental performance improvement opportunities for cost-effectiveness. For this reason, lighting represents one of the most promising opportunities for energy savings at airports, while the technologies used for lighting can greatly impact an airport's operational costs and sustainability programs.

Evaluating environmental impact mitigation through cost-effectiveness is crucial for (a) enhancing sustainability performance and (b) helping airport decision-makers manage facilities that have grown to resemble small cities in terms of size and services provided (Peneda *et al* 2011, Kidokoro and Zhang 2022). Despite progress in global airport sustainability programs, addressing lighting energy demands remains a persistent challenge because of the dual pressures of operational efficiency and environmental responsibility. Previous studies have demonstrated the utility of optimization methods for balancing environmental and economic trade-offs in transportation systems (Reger *et al* 2014, Kelle *et al* 2019), renewable energy supply chains (Hendrickson *et al* 2013, Chan *et al* 2022), and water distribution systems (Wu *et al* 2012, Zhang *et al* 2020). However, there is a critical need to extend these methodologies to airport lighting systems, where technological advancements can have far-reaching implications for energy consumption, cost, and overall sustainability.

To address this gap, we propose a model that integrates data envelopment analysis (DEA) and multi-criteria decision making (MCDM) techniques to identify the most sustainable lighting technology solutions. The DEA approach is well-suited to this challenge due to its capacity to handle diverse input-output scenarios and its ability to generate a single performance index that facilitates comparative evaluation (Sala-Garrido *et al* 2011, Mahmoudi *et al* 2019). Combining DEA with MCDM allows for a comprehensive assessment, ensuring that the selected technology not only performs efficiently but also aligns with broader sustainability objectives.

In the following sections, we present the details of this approach, beginning with the problem statement and our solution approach in section 2. In section 3, we apply the model to a real-world case study at the Dallas/Fort Worth International Airport (DFW), demonstrating its utility and potential for broader applications. Finally, section 4 concludes with key findings and directions for future research to advance airport sustainability through optimized lighting solutions.

2. Problem statement and solution approach

Although airports of various sizes worldwide are striving to incorporate sustainability into their planning and decision-making processes, there is limited research supporting these efforts. Some studies have developed a qualitative decision-making framework for determining effective emission reduction practices (Monsalud *et al* 2014, Greer *et al* 2020, 2021, Greer *et al* 2023, Sebos *et al* 2023), while other studies have used multi-objective optimization to reduce fuel consumption in airport ground operations (Weiszer *et al* 2015, Abbenhuis and Roling 2022). Additionally, some studies have developed methods for estimating the carbon footprint of equipment (Postorino and Mantecchini 2014, Loyarte-López *et al* 2020) or for benchmarking airport sustainability performance (Kilkis and Kilkis 2015, Kucukvar *et al* 2021). In this study, we expand on previous research and present a novel approach that utilizes life-cycle methodologies, case study data, and modeling for decision-making analyses to enhance the implementation of sustainability at airports.

The lighting technology data indicated that the data could be used as either inputs or outputs in a DEA model. Although some articles in academic literature guide the selection of the most appropriate DEA model (Cook *et al* 2014, Toloo *et al* 2021), this remains challenging due to the lack of a one-size-fits-all approach. We address this challenge by developing multiple DEA models, with the final decision being made by combining their outputs using the Simple Additive Weighting (SWA) method. Choosing the SAW method is logical, since the outputs of the DEA models represent efficiency values; therefore, summing their weighted values is a natural approach.

Instead of the SAW method, other well-known MCDM methods could have been used, such as the Technique for Order Preference by Similarity to Ideal Solution. However, the application of the SAW method in this study is the most effective and practical due to the nature of the DEA output values, as indicated above. Additionally, the SAW method is the simplest, yet effective, and does not require normalization. In contrast, applying the AHP method, for example, is much more complex because it involves subsequent pairwise comparisons that must be defined.

First, we define realistic DEA models that are tailored to address the specific challenges of our problem. Next, we evaluate the performance of each technology alternative using the defined DEA models to ensure a robust evaluation of their performance. Finally, we apply the MCDM technique (figure 1) to identify the best alternative technology. For this purpose, we employ the SAW method, where decision alternatives are the technology alternatives and criteria are the previously defined DEA models (figure 1).

2.1. DEA

DEA is a technique used to evaluate the relative efficiency of decision-making units (DMUs). It was created by Charnes *et al* (1978), whose model is widely known in the literature as the Charnes, Cooper, and Rhodes (CCR) model. This non-parametric approach is commonly used to measure the relative efficiencies of DMUs in schools, hospitals, or companies. Based on the reviewed academic literature (Cavaignac and Petiot 2017, de Oliveira *et al* 2023), DEA has been primarily used for evaluating system efficiency (of subsystems), and also for evaluating technology efficiencies. Khouja (1995) proposed a two-phase model for industrial technology selection, using DEA in both phases, in which the final selection was made using a multi-attribute decision-making model. A similar approach was adopted by Karsak and Ahiska (2005), who proposed a MCDM DEA approach for technology selection. Amin *et al* (2006) improved the model proposed by Karsak and Ahiska (2005). Sala-Garrido *et al* (2011) compared the efficiency of wastewater treatment technologies using the DEA meta-frontier model, while Pjevcevic *et al* (2016) applied the DEA model to select the most efficient scenario at the port container terminal, and Zhu (2022) applied the DEA model for data-oriented analytics in performance evaluation and benchmarking.

The DEA model is based on the linear programming method, where a linear program must be solved for each DMU. Solving the linear programs for each DMU can determine their relative efficiencies. There are numerous DEA models in the literature, and depending on the problem being solved, some models are more appropriate. The basic mathematical programming formulation for the input-oriented CCR model is presented in section S1 of the supplementary information.

2.2. SAW

The SWA method is one of the MCDM techniques. The simplicity of this approach makes it a popular choice. To briefly explain how this approach works, let us consider a matrix A_{mxn} in which element a_{ij} represents the value of alternative i per criterion j (table 1). Depending on these criteria, a_{ij} can take a broad range of values. Therefore, the values of the matrix A_{mxn} elements must be normalized (z_{ij}), that is, transformed to the [0,1] interval. One method to achieve this normalization is as follows:

- For the case with maximization criteria:

$$z_{ij} = \frac{a_{ij}}{\max\limits_{k=1,\ldots,m} \left\{a_{kj}\right\}}. \tag{1}$$

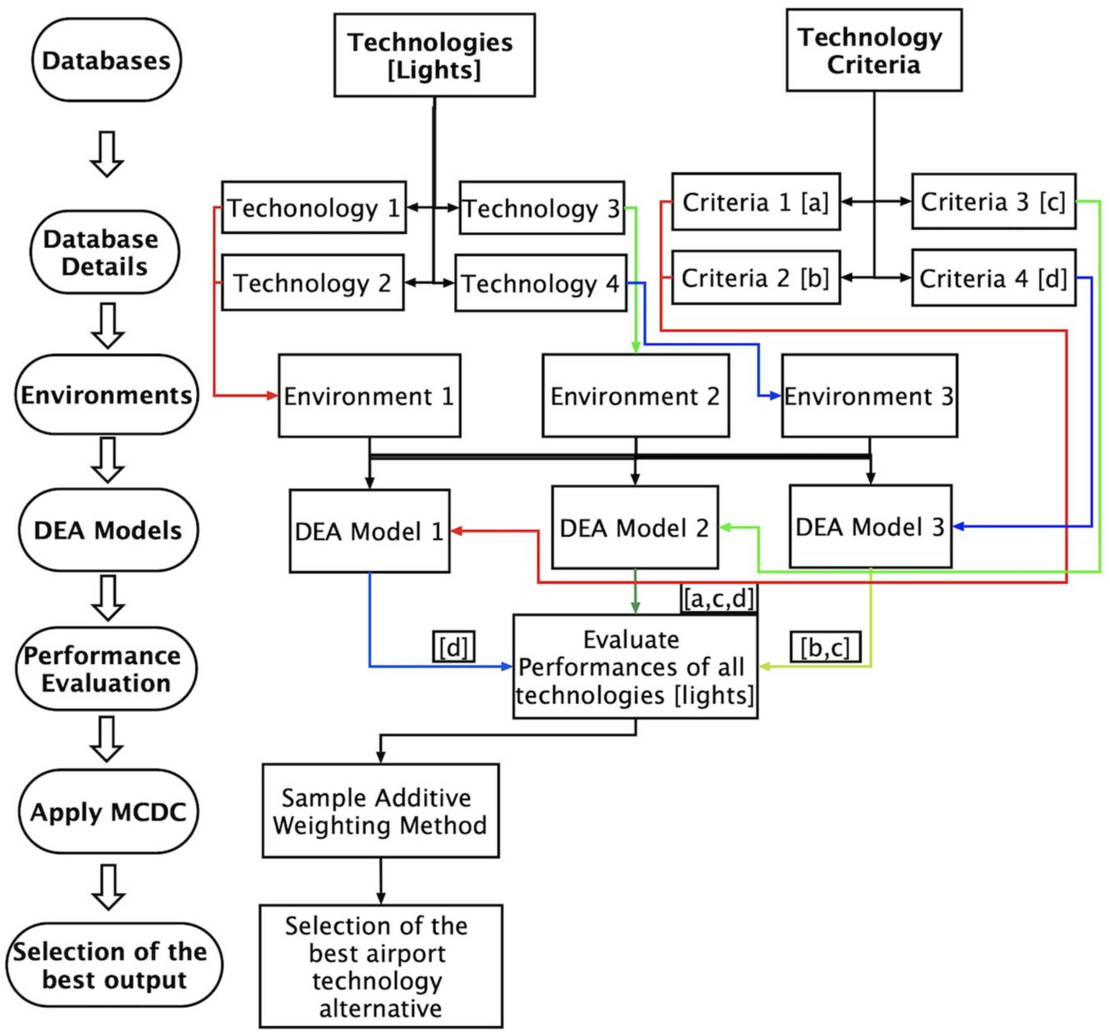

Figure 1. A general method for selecting the most sustainable airport technology.

Table 1. Input data for the simple additive weighting method.

		Criteria j					
		1	2	....	j	....	n
Alternative i	1	a_{11}	a_{12}		a_{1j}		a_{1n}
	2	a_{21}	a_{22}	....	a_{2j}	....	a_{2n}
	....	....	....		....		....
	i	a_{i1}	a_{12}	....	a_{ij}	....	a_{in}
	....	....	....		....		....
	m	a_{m1}	a_{m2}	....	a_{mj}	....	a_{mn}

- For the case with minimization criteria:

$$z_{ij} = \frac{\min\limits_{k=1,\ldots,m} \left\{a_{kj}\right\}}{a_{ij}}. \tag{2}$$

Sometimes, the criteria do not carry the same level of importance. If W_j denotes the weight of criterion j, then the normalized weights of the criteria can be calculated as

$$w_j = \frac{W_j}{\sum_{k=1}^{n} W_k}. \tag{3}$$

For each alternative ($i = 1, \ldots, m$), the weighted sum (V_i) is calculated as

$$V_i = \sum_{j=1}^{n} w_i z_{ij}. \tag{4}$$

According to value V_i, alternatives can be ranked in decreasing order (from the highest value to the lowest value of V_i), where the best alternative is the first one, and the worst is the last one.

3. Application to lighting sustainability

DFW was selected as the case study. DFW is located in the state of Texas, USA, and is one of the busiest and largest airports in the country. It covers more than 27 square miles (roughly 17 250 acres). The size and operational complexity of DFW make it a strong candidate for evaluating energy-intensive technologies such as lighting systems (Leatherwood and Marshall 2025).

This study examined eight lighting solution technologies, each with five alternatives. There is a total of 40 lighting technology solution alternatives that can be implemented. For each alternative, values were provided for eight criteria: luminous flux (lm), capital cost ($), life-cycle cost ($), energy consumption (kWh), and four types of emissions [(kg) CO_2e, NO_x, SO_2, and $PM_{2.5}$].

The data used in this research were collected using a combination of documents from major lighting manufacturers, published literature on airport lighting technologies, and publicly available airport operations and sustainability reports.

The environmental and economic performances of the different lighting technologies used in airport infrastructure systems were calculated using life-cycle cost accounting (LCCA). This method is a holistic technique for determining product outputs over the entire product lifecycle. This assessment uses LCCA to estimate costs, energy consumption, and emissions for eight different lighting technologies (single fixture) in operation over a 30-year analysis period.

The assessment is based on lighting technology specifications (i.e. pricing, efficacy, and lifetime) as found in the related literature and manufacturers' data from 2024. Table 2 lists the data sources and the values of these specifications.

Capital costs reflect the supplier prices. In the LCCA calculations, emissions were not monetized. Instead, LCCA covers direct financial costs such as capital and energy, and assumes a discount rate of 4% for these costs over the analysis period. Emissions (kg) [CO_2e, NO_x, SO_2, and $PM_{2.5}$] were evaluated separately as environmental performance criteria in the DEA models. This allows the decision-making process to account for environmental impact explicitly without folding it into monetary terms, which can vary widely depending on the valuation method or regulatory context. The lighting fixture replacements are also estimated based on the total assumed lighting requirements for both indoor and outdoor environments. Electricity consumption estimates were adjusted using the 2022 Texas state-wide electricity mix, as reported by the U.S. Energy Information Administration. The state mix was used because detailed utility-level data for DFW's service territory is not publicly available. The Texas mix captures the primary generation sources (natural gas, wind, and coal) that feed the airport and therefore serves as a reasonable proxy. Daily operational hours (15 h d^{-1} for outdoor, and 24 h d^{-1} for both (a) indoor and (b) indoor & outdoor environments) were standardized across all lighting types to ensure consistent comparisons.

For operations, economic and environmental outputs were estimated based on product energy ratings (W) and lighting needs to obtain the total energy requirements (kWh). Energy ratings were based on product efficacy and the required luminous flux in the design. The assessment applied the total energy demand to the electricity mix of the case study (Texas average state mix). Electricity mix projections over a 30 year analysis period were based on the EIA's annual energy outlook 2022, Reference Case for the Texas Reliability Entity region. The Reference Case reflects EIA's baseline assumptions about technology costs, energy policies, and fuel prices, and was selected as a neutral benchmark for estimating long-term trends in emissions intensity (EIA 2022). The average of the normalized metric values is shown in figure 2. We can observe that the standard incandescent light technology has the highest average values across all metrics (kWh, $kgCO_{2e}$, life-cycle cost ($), and capital cost ($)), followed by halogen, while the low pressure sodium light technology has the lowest average normalized values across all metrics except the capital cost, which is lower with the LED light technology.

Table 2. Specifications and data sources for the lighting technologies assessed.

Technology[a]	Environment	Efficacy (lumen/watt)	Lifetime (hours)
LED T8	Both	130	50 000
Fluorescent T8	Both	60	24 000
High-pressure sodium	Outdoors	90	30,000
Low-pressure sodium	Outdoors	180	18 000
Induction	Both	175	50 000
Metal Halide	Both	80	15 000
Std Incandescent	Indoors	10	2,000
Halogen	Both	18	2,000

[a] The 90th percentile of either SATCO®-qualified products (light emitting diode (LED) T8, Fluorescent T8, High-pressure sodium (HID ET18), Metal Halide (HID ED 28), Standard Incandescent BR40, and 1/2 Halogen Incandescent T4) or Philips-qualified products (Low-pressure sodium (SOX T17), and Induction Lighting) was used to characterize the efficacy of 'top-performing' products. Then the average prices were found for products at this efficacy point. SATCO® is an American standard for energy-efficient consumer products, founded in 1966, and is well known as the premier supplier of a variety of lighting products.

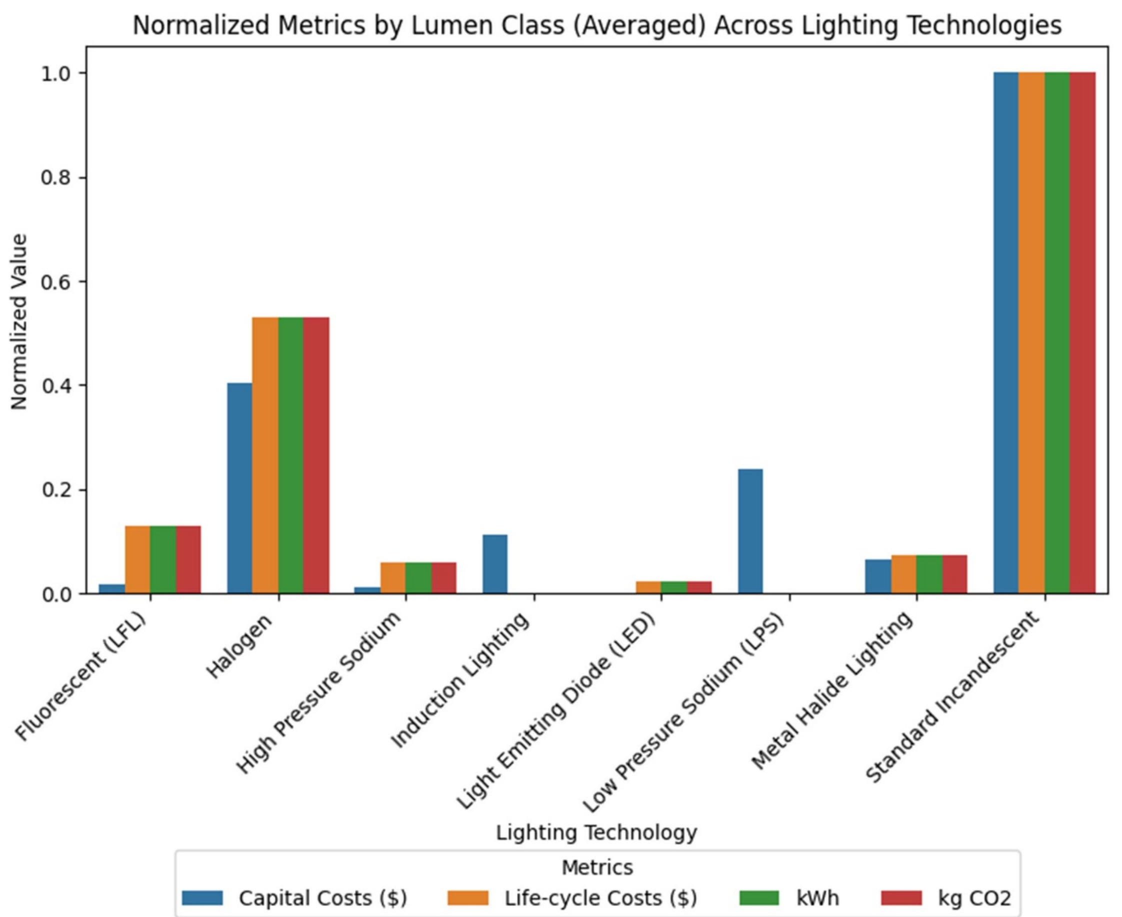

Figure 2. Normalized comparison of lighting technologies across four metrics: capital cost, life-cycle cost, energy use (kWh), and CO_2 emissions. Values are normalized (0–1) within each lumen category to allow visual comparison of performance across metrics.

3.1. Model development

We consider three DEA models for the application to airport lighting technologies using the efficiency measurement system (EMS) software to solve all DEA models. The solutions obtained are shown in figures 3–5.

3.1.1. Model 1: an input-oriented CCR model with seven inputs and one output

Model 1 is an output-oriented CCR model with seven inputs and one output (luminous flux). The mathematical formulation of this model is as follows (based on Cooper *et al* (2006)):

$$\min_{\theta,\lambda_j} \quad \theta$$
$$\text{s.t.} \tag{5}$$

$$\theta x_{io} - \sum_{j=1}^{n} x_{ij}\lambda_j \geqslant 0 \qquad i = 1, \ldots, m \tag{6}$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j \geqslant y_{ro} \qquad r = 1, \ldots, s \tag{7}$$

$$\lambda_j \geqslant 0 \qquad j = 1, \ldots, n \tag{8}$$

where:
n—the number of DMUs,
m—the number of inputs,
s—the number of outputs,
j—index of DMU, $j = 1, \ldots, n$,
i–index of input, $i = 1, \ldots, m$,
r—index of output, $r = 1, \ldots, s$,
x_{ij}—ith input of decision unit j,
y_{rj}—rth output of decision unit j,
λ_j—weight of DMU j (decision variable)
θ—level of input (decision variable)

The objective function (5), which represents the level of input, is minimized. Constraint (6) guarantees that the input of the virtual DMU ($\sum_{j=1}^{n} x_{ij}\lambda_j$) will not be greater than the input of the observed DMU (x_{io}) multiplied by the decision variable input level (θ). Constraint (7) states that the output of the virtual DMU ($\sum_{j=1}^{n} y_{rj}\lambda_j$) must be equal to or greater than the output of the observed DMU (y_{ro}). The decision variables must be non-negative because of constraint (8).

This model evaluates the performance of different lighting technologies by focusing on minimizing resource use and environmental impacts, while delivering a given amount of luminous flux. In this model, the seven inputs considered are capital costs, life-cycle costs, energy consumption, and four types of emissions. The goal is to determine which technologies use the least resources and produce the lowest

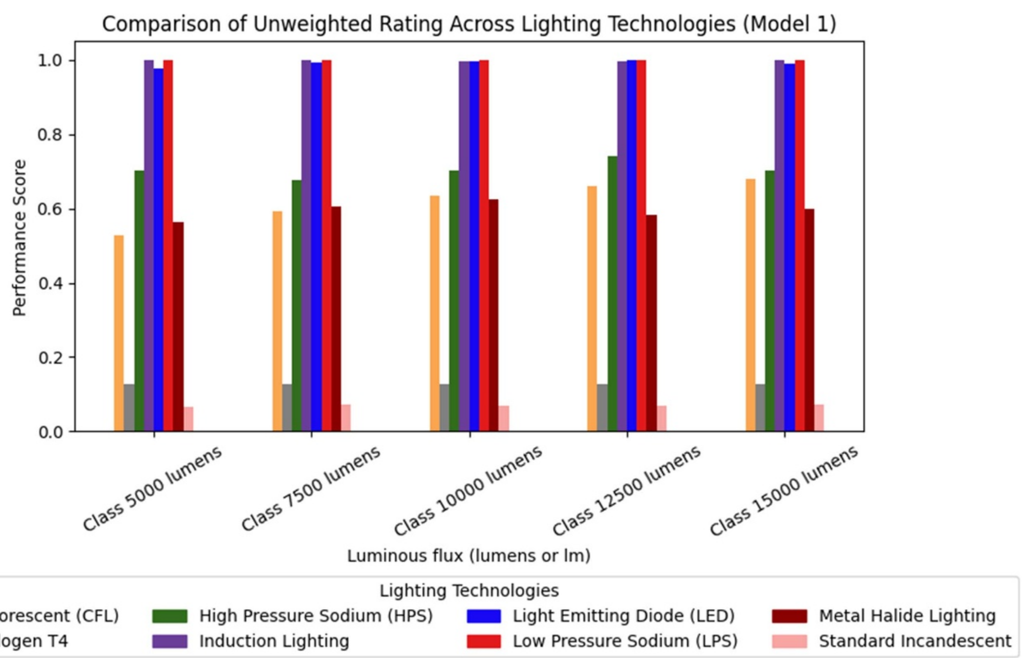

Figure 3. Unweighted performance score across lighting technologies for various luminous flux (Model 1).

emissions for the same level of light output. Figure 3 shows the performance of the seven lighting technologies for five different classes of luminous flux. Across all five cases, standard incandescent lighting had the lowest relative efficiency, followed by halogen, metal halide, fluorescent, light emitting diode, induction lighting, and high pressure sodium. The most efficient technology was low pressure sodium lighting.

3.1.2. Model 2: an output-oriented CCR model with one input and seven outputs

Model 2 is an output-oriented CCR model, with one input (capital cost) and seven outputs. The mathematical formulation of this model is based on Cooper *et al* (2006):

$$\max_{\eta,\,\mu_j} \eta \quad \text{s.t.} \tag{9}$$

$$x_{io} - \sum_{j=1}^{n} x_{ij}\,\mu_j \geqslant 0 \quad i = 1, \ldots, m \tag{10}$$

$$\eta\, y_{ro} - \sum_{j=1}^{n} y_{rj}\mu_j \leqslant 0 \quad r = 1, \ldots, s \tag{11}$$

$$\mu_j \geqslant 0 \quad j = 1, \ldots, n \tag{12}$$

where:
μ_j—weight of DMU j (the decision variable),
η—level of output (decision variable).

The objective function (9) maximizes the output level. Constraint (10) guarantees that the input of the virtual DMU ($\sum_{j=1}^{n} x_{ij}\,\mu_j$) will not be greater than the input of the observed DMU (x_{io}). The output of the virtual DMU ($\sum_{j=1}^{n} y_{rj}\mu_j$) must be at least equal to the output of the observed DMU (y_{ro}) multiplied by variable η, which represents the level of output. This is defined by constraint (11). Constraint (12) defines the decision variables as nonnegative.

In the second model, the focus shifts to maximizing outputs for a fixed input. Here, capital cost is the sole input, while the outputs include lumens, life-cycle costs, energy consumption, and emissions (see table 3 in the appendix). The model examines how effectively each lighting technology converts its capital cost into benefits such as light output and reduced environmental impacts. It identifies the

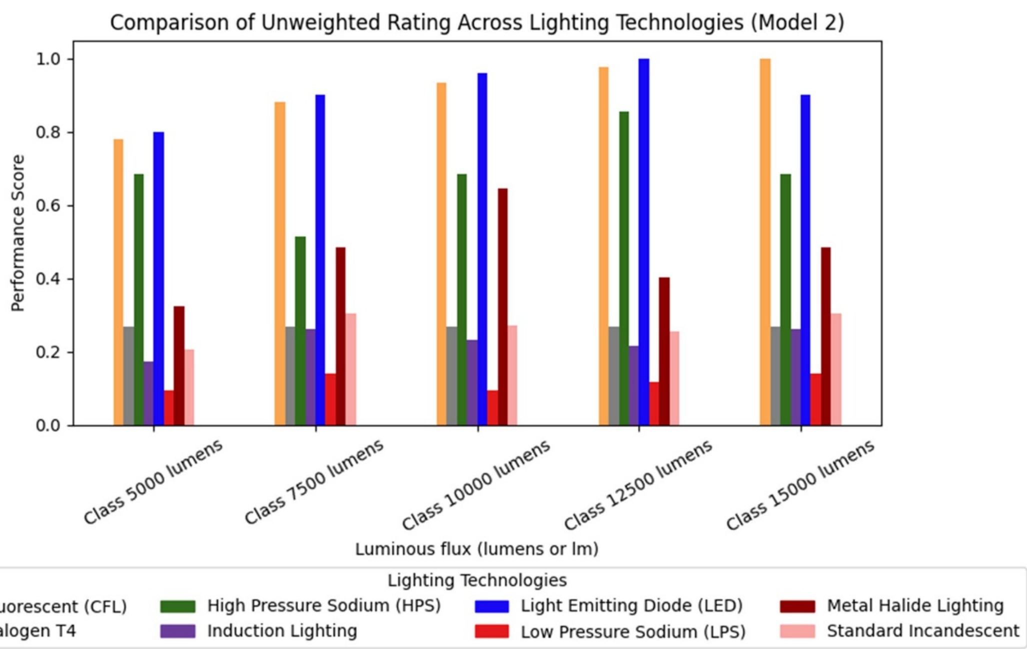

Figure 4. Unweighted performance score across lighting technologies for various luminous flux (Model 2).

technologies that provide the greatest returns in terms of light and sustainability for the same level of investment.

The performance scores of the lighting technologies shown in figure 4 indicate significant variations in the unweighted performance across different levels of luminous flux. Among these technologies, LED, fluorescent lighting, and high-pressure sodium demonstrate a higher performance across all luminous flux levels compared to other lighting technologies. At 15 000 lumens, fluorescent was the best performer, followed by LED, then high-pressure sodium. The LED occupies first place in the first four lumens classes, followed by fluorescent lighting, then high-pressure sodium lighting. Low-pressure sodium, induction, and standard incandescent lighting consistently performed low throughout all luminous flux levels.

3.1.3. Model 3: an output-oriented CCR model with two inputs

Model 3 is an output-oriented CCR model (9)–(12), with two inputs (luminous flux and capital cost) and six outputs. When inputs and outputs are in undesirable forms (inputs should be minimized and outputs maximized), inverse data transformation is used (Golany and Roll 1989, Scheel 2001, Seiford and Zhu 2002, Amiri and Sangar 2023).

This model evaluates the balance between luminous flux and capital costs as two inputs while considering six outputs: life-cycle costs, energy consumption, and four types of emissions. The model assesses the efficiency of lighting technologies in minimizing costs and environmental impacts for a given combination of light output and capital investment. This highlights technologies that offer the best trade-offs between performance and sustainability.

The performance scores of the lighting technologies shown in figure 5 illustrate a notable variation in the unweighted performance across different levels of luminous flux. All lumen classes have closely related performance metrics at every flux level. As the two inputs produce a similar performing output for all lumen classes, the selection of a specific technology is reduced to the luminous flux needed, knowing that standard incandescent is the best performing technology and LPS the worst across all five luminous flux levels.

Each model provides a unique perspective for identifying the most efficient lighting technology based on the specific criteria discussed above. Figure 6 shows the average performance of the three models. Model 3 shows the highest performance among the two (out of eight) lighting technologies, while Model 1 shows the highest performance among the three lighting technologies (LED, induction, and low-pressure sodium). All technology alternatives and emission values are shown in table 3 and are located in the appendix.

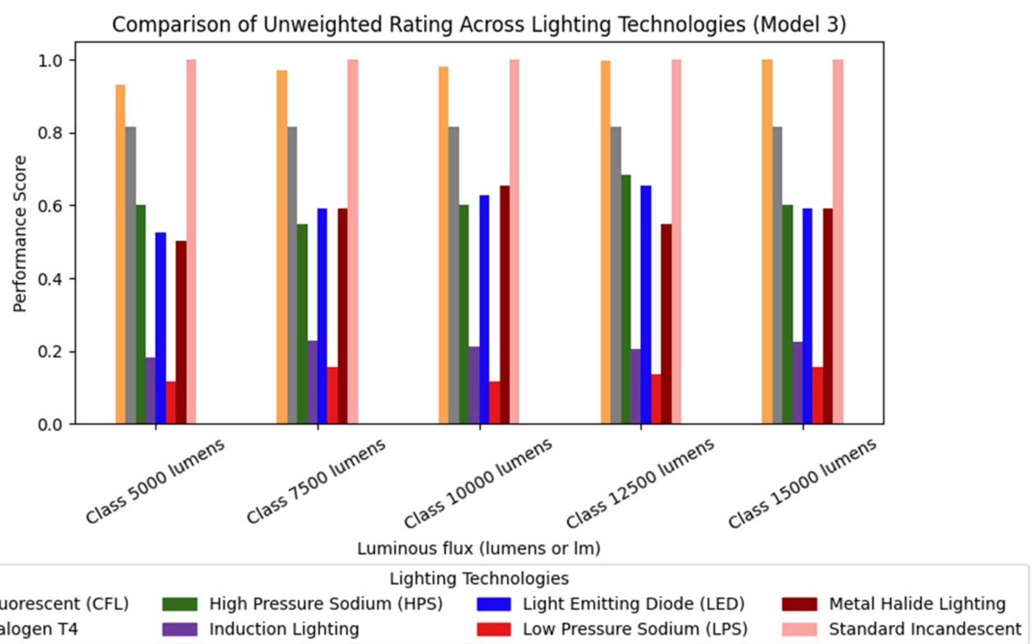

Figure 5. Unweighted performance score across lighting technologies for various luminous flux (Model 3).

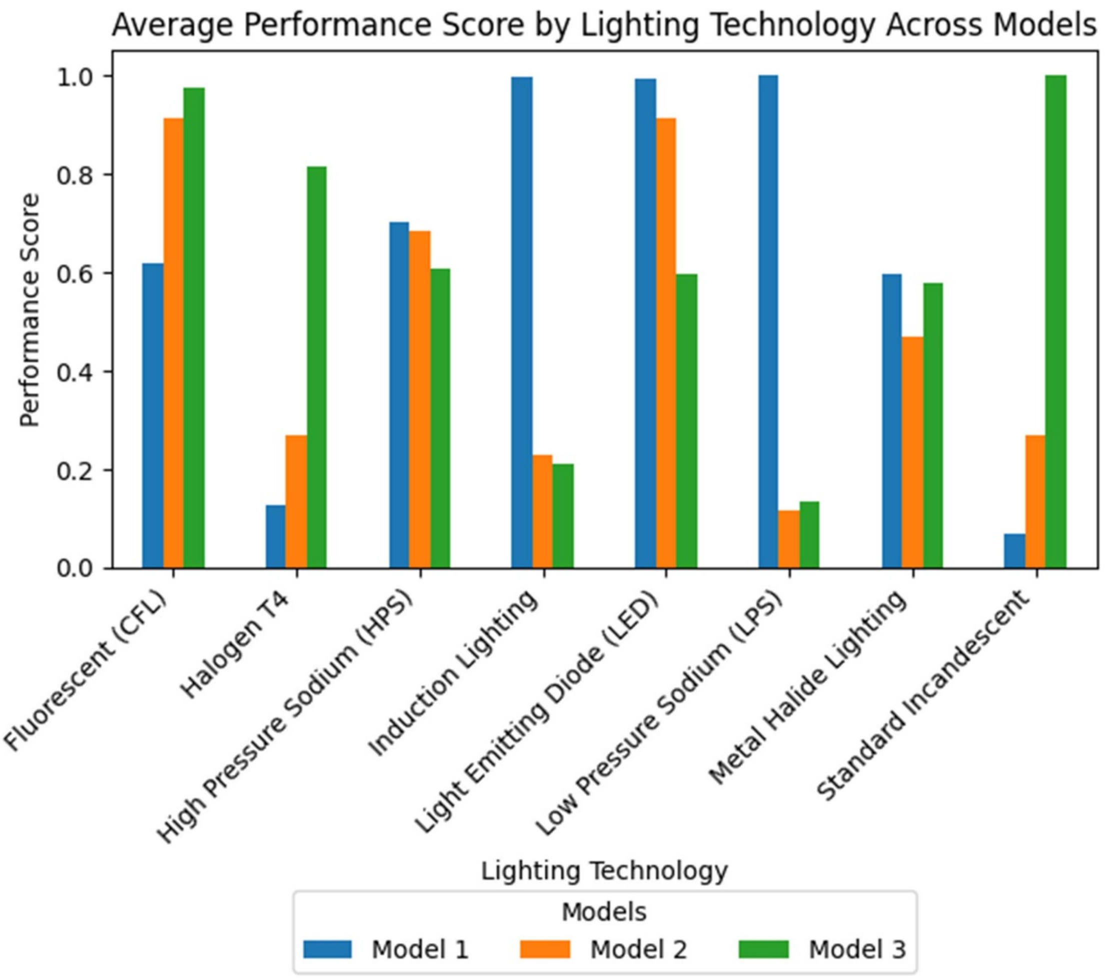

Figure 6. Average performance of lighting technologies across all models.

The average performance scores of the lighting technologies for the three models shown in figure 6 demonstrate specific trends. For technologies such as low pressure sodium, induction, and LED, Model 1 has higher performance, whereas Model 2 shows lower performance in those technologies. In contrast, for halogen and standard incandescence, Model 2 outperformed Model 1, while Model 3 maintained higher performance for standard incandescent, fluorescent, and halogen lighting, as discussed above.

3.2. Application of the MCDM method to a real-world case study at DFW

Figure 7 illustrates the application of the general model depicted in figure 1 to a real-world case study at the DFW airport.

Because the maximal value for each DEA model in figures 3–5 is equal to 1, the normalization step in the SAW method does not alter their values. It is assumed that there are no preferences between these DEA models, that is, the weights W_j for all criteria are equal ($W_1 = W_2 = W_3 = 1$). This is one of the common approaches in the literature for determining weights when authors do not wish to favor any particular criterion subjectively, or when they consider them to be of relatively equal importance. In this analysis, it did not seem reasonable to favor any one of the three models, as all were deemed suitable for the analysis. Therefore, the normalized weights were $w_1 = w_2 = w_3 = 0.3333$.

To ensure consistency, we accounted for the differences in the operating times between the technologies. High-pressure and low-pressure sodium lighting, which operated for 15 h (h) per day, were adjusted to match the operating weights of the other lighting technologies. This was achieved by applying a factor of $\frac{15}{24}$ to the performance score values.

With these adjustments, the weighted sum (V_i) for each alternative can be calculated using equation (4). The weighted sums obtained are presented in figures 8–10. The weighted performance score values derived using the SAW method are shown in figure 11.

The first model mirrors the structure of the unweighted Model 1, focusing on minimizing resource use and emissions while delivering a specified luminous flux. The performance scores from the

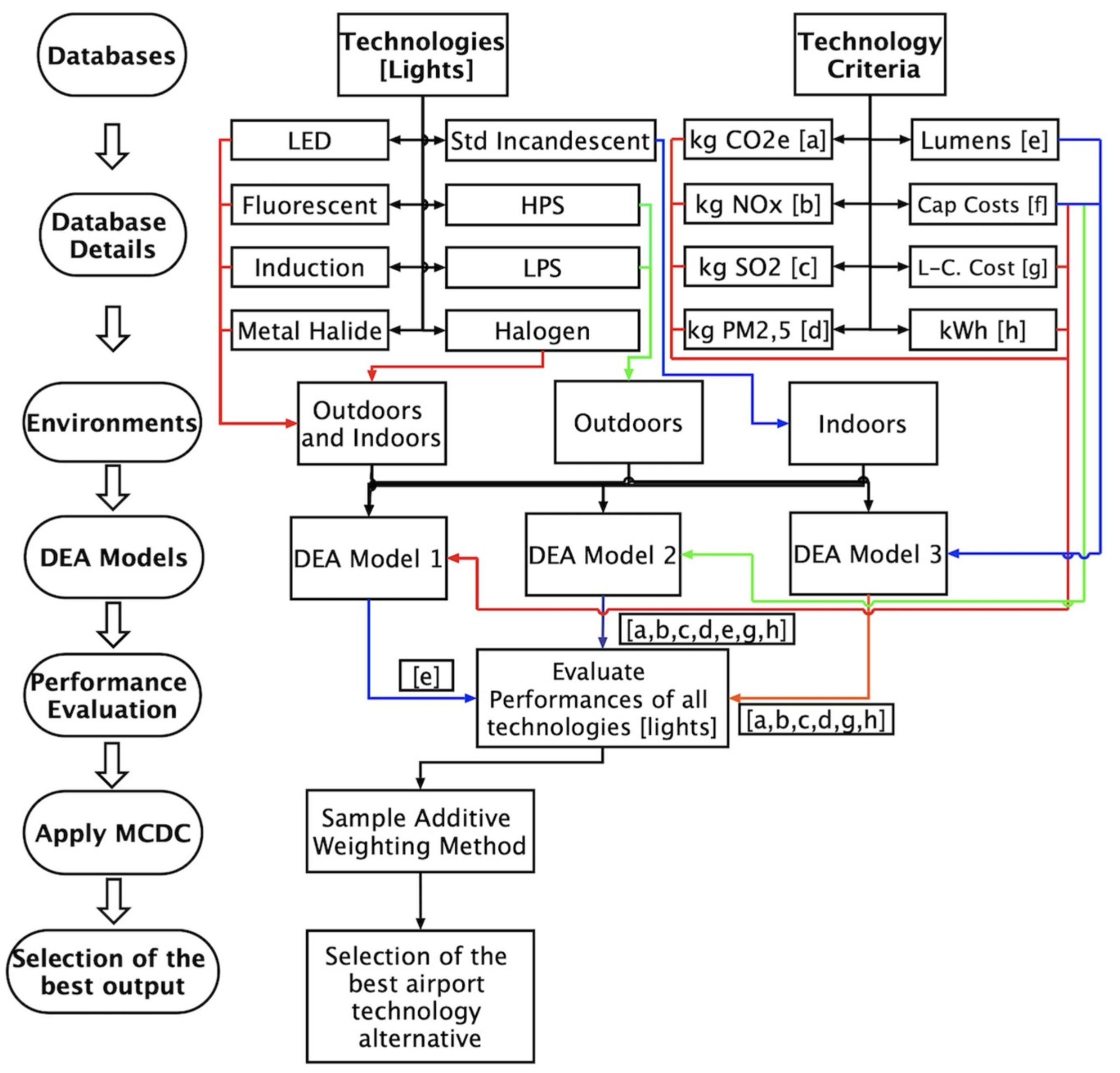

Figure 7. A proposed general method applied to DFW.

unweighted analysis were normalized using the SAW method. Because the highest score for each DEA model was 1, normalization did not alter the values. Equal weights ($w1 = w2 = w3 = 0.3333$) were applied to ensure no preference for any specific DEA model. Additionally, a correction factor ($\frac{15}{24}$) was applied to adjust the performance scores of high-pressure and low-pressure sodium lighting, accounting for their longer operational times compared to other technologies. This adjustment ensures consistency and fairness across technologies with varying operating conditions. The weighted performance scores for Model 1, as calculated using equation (4), are shown in figure 8.

Lighting technologies are being compared based on equal functional output, specifically fixed luminous flux levels. For each DEA model and SAW ranking, performance is assessed within defined output classes (e.g. 5000 lumens, 7500 lumens, etc.). This ensures that the lighting types serve the same function and align with the principles of life-cycle assessment. Each technology is evaluated based on how efficiently it delivers a given amount of light, using consistent operating hours and environmental assumptions.

The performance scores of the lighting technologies shown in figure 8 reveal that the weighted performance remains consistent across different levels of luminous flux, similar to unweighted Model 1. Induction and LED technologies exhibit the highest performance. However, halogen and standard incandescent ranked the lowest across all flux levels.

The goal is not to rank lighting technologies in general, but to identify which options are the most efficient and sustainable within specific application contexts, such as where a known lighting requirement exists (e.g. a garage level, terminal concourse, or airside ramp).

In the second model, the emphasis is on maximizing outputs (e.g. luminous flux and environmental benefits) for a fixed input (capital cost). Similar to Model 1, the SAW method and operational time

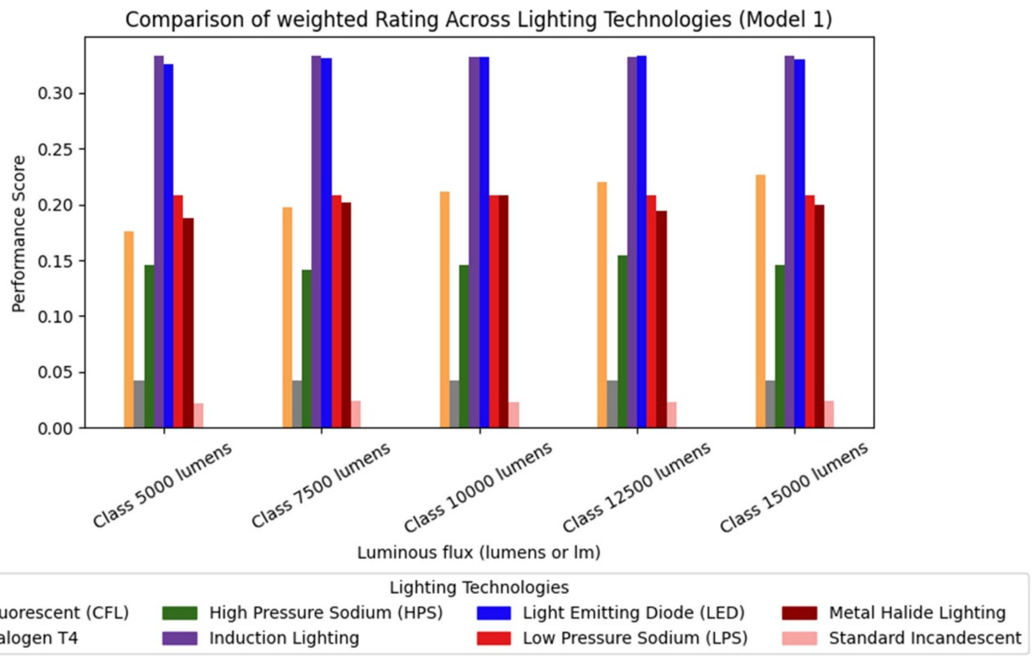

Figure 8. Weighted performance score across lighting technology for various luminous flux (Model 1).

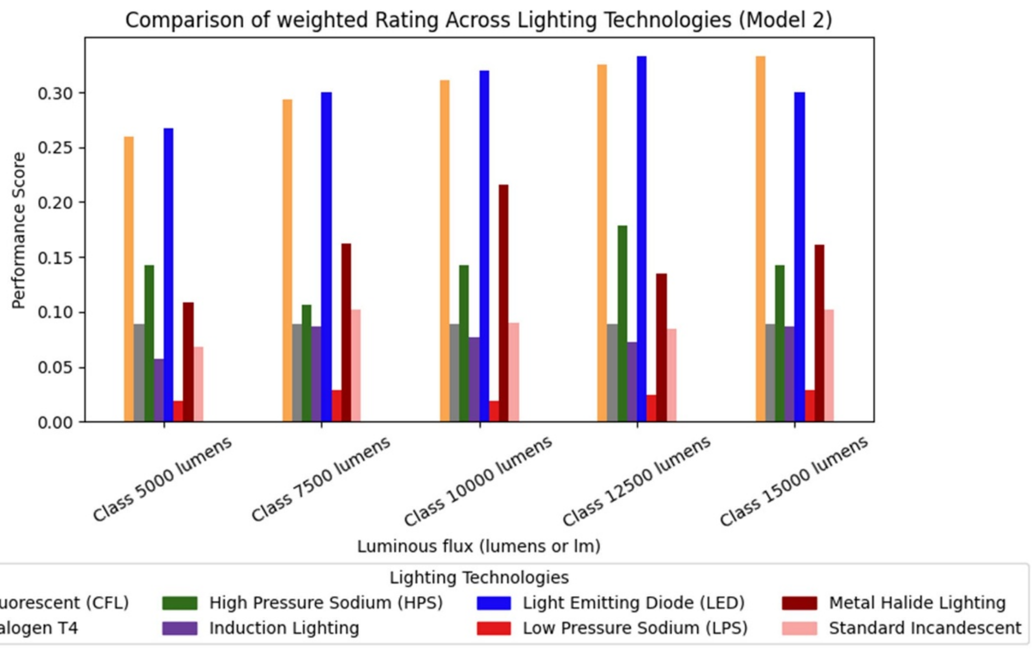

Figure 9. Weighted performance score across lighting technology for various luminous flux (Model 2).

adjustment were applied to unweighted performance scores. The weighted sum (V_i) for each alternative captures the balance between capital investment efficiency and the resulting benefits. These weighted performance scores of lighting technologies are illustrated in figure 9, indicating significant variation in weighted performance across different levels of luminous flux. Among these technologies, LED and fluorescent demonstrate the highest performance below 15 000 lumens with LED being the best. Beyond this point, fluorescent lighting switches places with LED. The third-ranking technology shifts depending on the luminous flux level. High pressure sodium takes the third place at 5000 and 12 500 lumens, metal halide at 7500, 10 000 lumens, and 15 000 lumens. Low-pressure sodium and induction lighting remain consistently lower performing throughout all luminous flux levels, similarly to the unweighted Model 2.

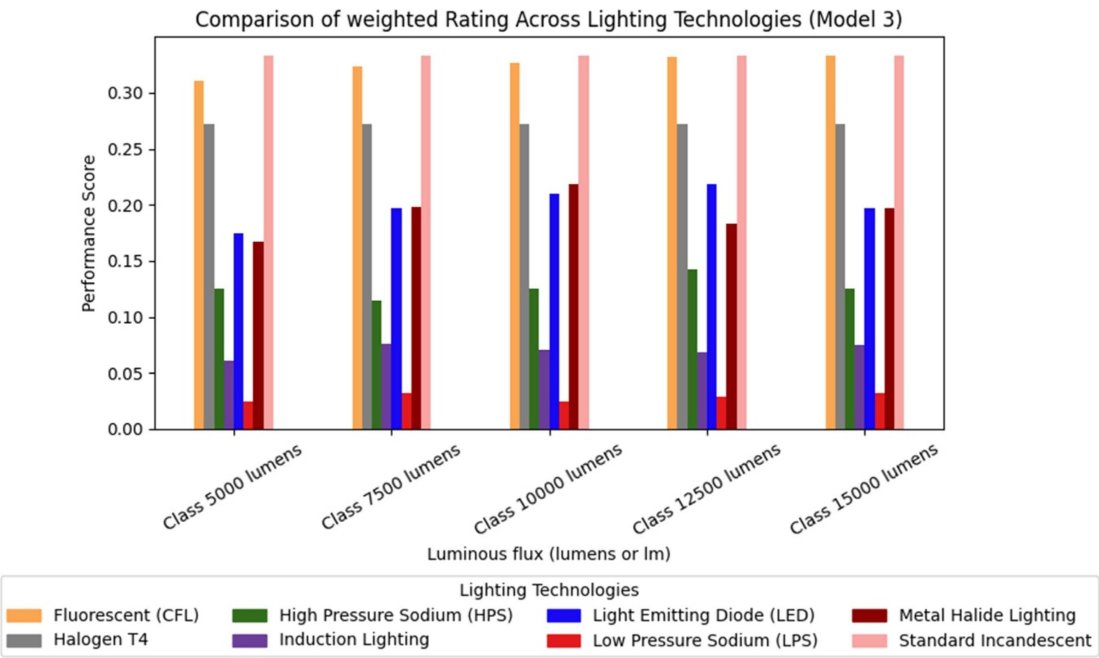

Figure 10. Weighted performance score across lighting technology for various luminous flux (Model 3).

Model 3 evaluates the trade-offs between two inputs (luminous flux and capital cost) and six outputs (life-cycle costs, energy consumption, and four types of emissions). The SAW method and operational time adjustment were again used to assign equal importance to the criteria. This ensures that all the technologies are evaluated on a comparable basis. The resulting weighted performance scores are shown in figure 10.

The weighted performance scores presented in figure 10 highlight the minimal shifts in performance rankings across different luminous flux levels. The top three technologies (standard incandescent, fluorescent, and halogen) have very similar performance values in different flux levels. Similarly, the bottom three technologies (high-pressure sodium, induction, and low-pressure sodium) also have similar performance values across different flux levels. The variation in rank occurs between LED and metal halide, with LED dominating in the 5000 and 12 500 lumen classes while metal halide lighting takes 4th place in 7500, 10 000, and 15 000 lumen classes. Like the unweighted Model 3, the selection of one technology over another among the six will be a matter of the luminous flux levels needed and the best-performing technology for the specific flux level.

The weighted performance scores derived from the SAW method for all three models were consolidated and are shown in figure 11. This final step integrates the adjustments for operating times and equal weighting of criteria, providing a comprehensive view of the relative performance of lighting technologies across varying luminous flux levels.

Weighted analysis highlights technologies that balance performance and sustainability by considering both their unweighted performance scores and adjustments for operational realities.

The weighted performance scores shown in figure 11 illustrate the overall dominance of LED lighting across all luminous flux levels, except for the 15 000 lumen class, which ranks second. Fluorescent and metal halide lighting showed high performance across all lumen classes, respectively. Fluorescent lighting remained in second position until the 15 000 lumen class, where it gained the first rank. Meanwhile, halogen, high-pressure sodium, and low-pressure sodium consistently occupy lower ranks across all flux levels.

As shown in figure 12, ranking was conducted across the different luminous flux classes. For the 5000 lumen class, the results indicate that LED lighting ranked first, followed by fluorescent lighting, metal halide lighting and induction lighting. Notably, the LED retained its top position across the first four classes (5000, 7500, 10 000, and 12 500 lumens). However, a shift occurred in the 15 000 lumen class, where fluorescent lighting switched places with LED lighting, whereas low-pressure sodium lighting remained consistently lower ranked.

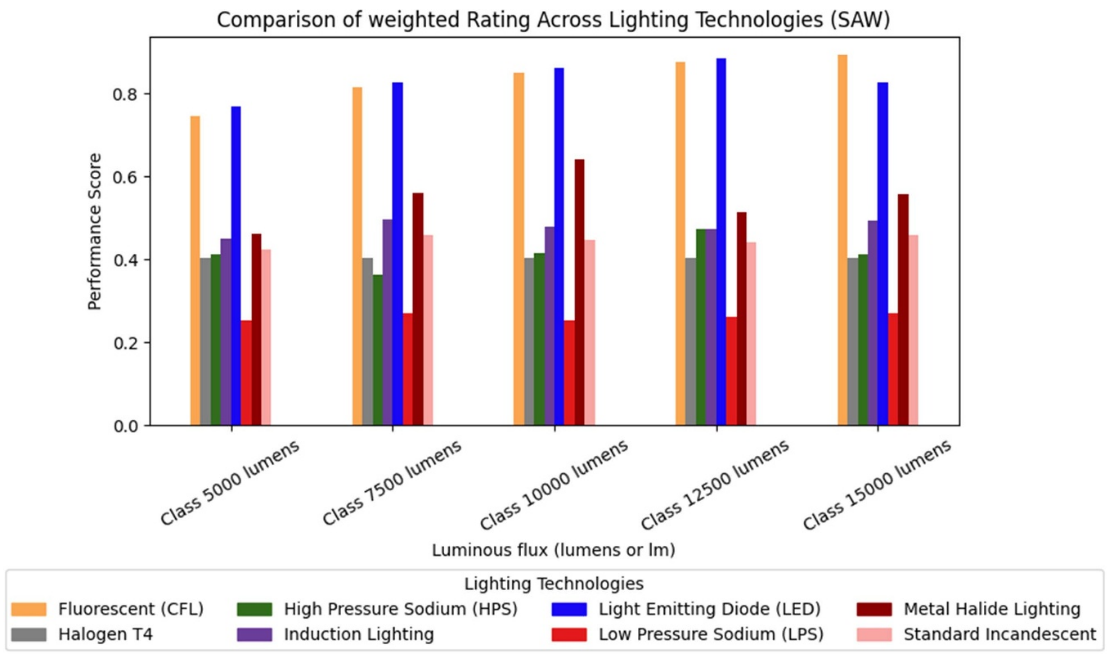

Figure 11. Weighted performance score across lighting technology for various luminous flux (SAW).

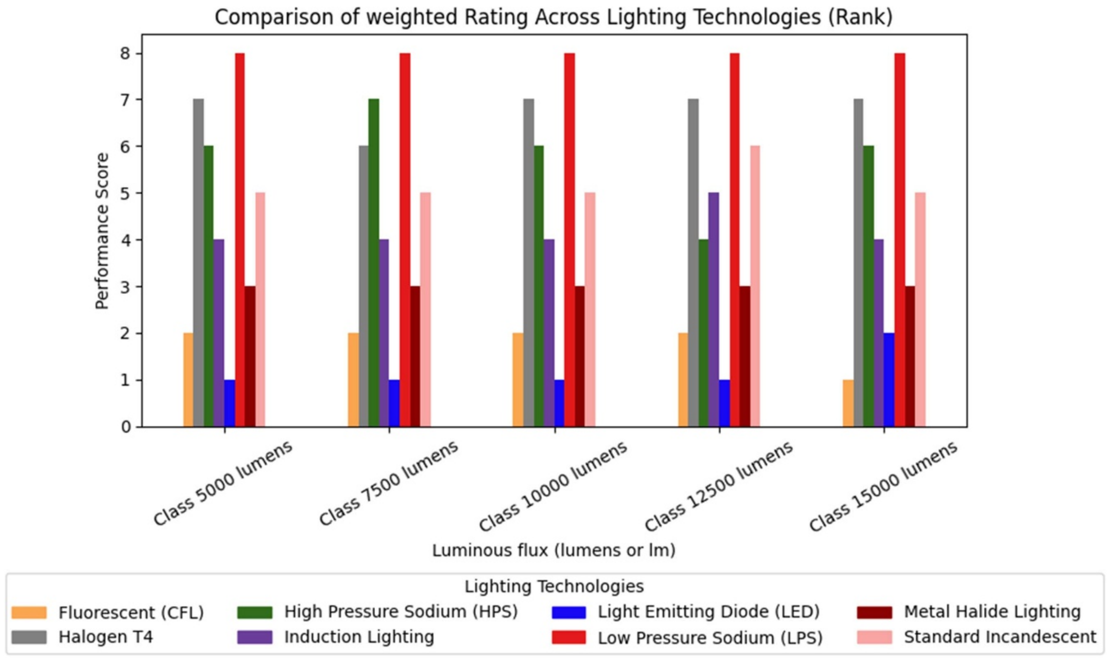

Figure 12. Performance ranking across lighting technology for various luminous flux classes.

Throughout the ranking, low-pressure sodium and halogen lighting consistently occupied the lowest positions, reinforcing their limited effectiveness as sustainable alternatives in comparison to other technologies.

A sensitivity analysis was conducted to test the robustness of the model's output by varying the weights assigned to each DEA model in the SAW method. The original model assigned equal weights to the three DEA models ($w_1 = w_2 = w_3 = 0.3333$). Three additional scenarios were run, where each model was given greater weight (0.5) while the other two shared the remaining 0.5 equally. The results indicate that certain technologies, such as LED and induction lighting, maintain relatively stable

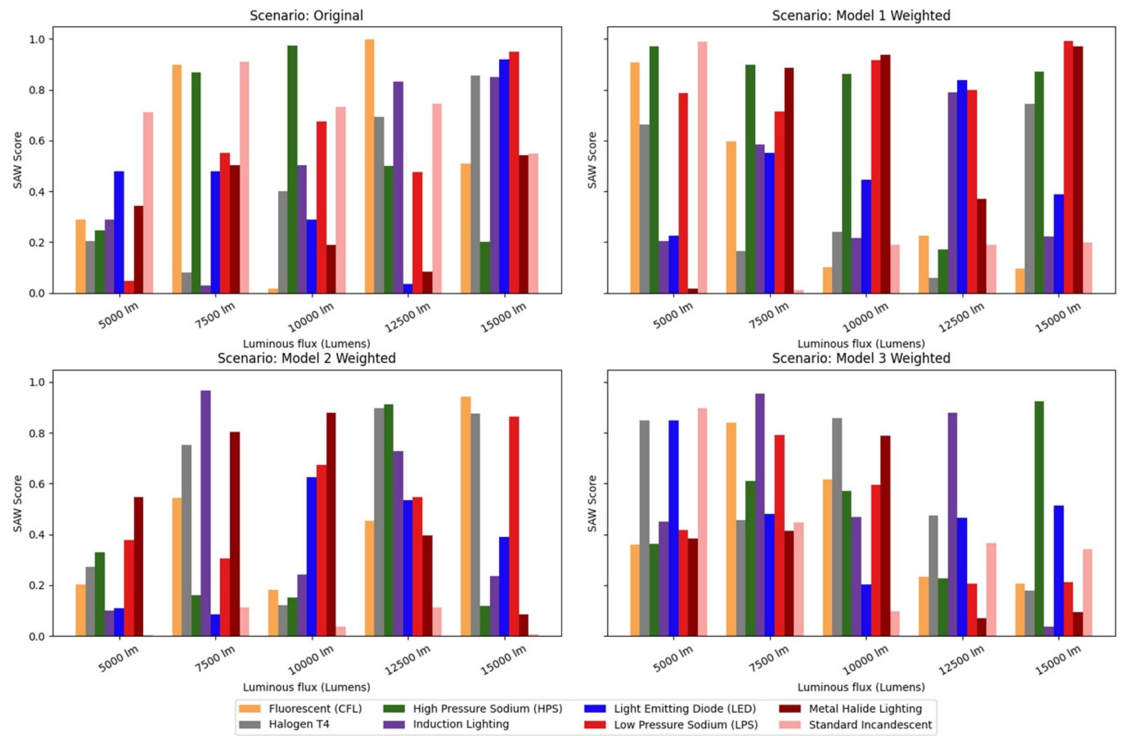

Figure 13. Sensitivity analysis of lighting technology performance scores under varying DEA model weights in the SAW method.

scores across scenarios, while others exhibit significant variation. For example, the performance score of Halogen T4 or LPS varies greatly depending on the DEA model prioritized, as shown in figure 13.

These variations show that the model is sensitive to the assigned weights. This implies that the choice of DEA weighting influences the final rankings and reveals the importance of considering multiple weighting options when recommending lighting technologies.

4. Conclusions

This study proposes a comprehensive model for selecting technology alternatives using DEA and MCDM techniques. The proposed approach was tested in a real case study focusing on the selection of lighting technologies at the DFW. To solve this problem, three DEA models and the SAW method were used. The EMS software was used to solve the DEA models.

This study primarily focuses on the economic and environmental dimensions of sustainability, as those can be quantitatively modeled across technologies. The social dimension is not directly captured in this model but remains critical in real-world airport decisions. The lighting technology solution alternatives were ranked according to the analysis results shown in figure 12. However, some limitations can be overcome to obtain more accurate results. The first limitation involves comparing all selected lighting technologies. An assumption was made regarding the daily operation time for both the indoor and outdoor environments. Separating and analyzing these environments based on their specific needs might provide different results. The second limitation is the consideration of lighting across the entire airport, rather than breaking it down into different airport infrastructure elements. Various parts of an airport might require different lighting criteria. The third limitation was the selection of light bulbs. We focus on the most common bulbs for each lighting technology. As the analysis results depend on these bulb criteria, choosing different bulbs would produce different results. Another limitation was the use of a Texas state-wide grid mix rather than an airport-specific electricity profile, which provided a broad picture of regional generation sources instead of highlighting differences in emissions intensity that a facility-level profile could reveal. Future research should extend the proposed method to account for the specific objectives of each airport's infrastructure when selecting light bulbs; they should also include social factors, either through qualitative scoring or integration with operational feedback from airport facilities staff. In addition, cases in which multiple alternatives have the same values should be addressed. A suitable sensitivity analysis approach should be proposed in future research.

The implementation of new technologies can reduce negative environmental effects at airports. Large airports with significant revenue streams have a greater capacity to implement innovative technologies to drive sustainability goals, where other infrastructures struggle in this regard (Dhakal *et al* 2017). As described in the weighting methodology, airports differ in their sustainability criteria, as regional characteristics and budgets can vary substantially. The SFO's program for increasing wastewater recycling is a good example, which is valuable in the SFO's drought-prone region but may be cost-prohibitive for airports without significant drought concerns (SFO 2020). These technologies can vary substantially for certain facilities over time and in different regions. These considerations should be taken into account when implementing decision support models at airports and when advancing this research into new applications.

Based on the combined DEA and MCDM analysis across five luminous flux levels, LED lighting consistently outperformed the other technologies and emerged as the most sustainable option overall, balancing low energy consumption, long life cycle, and competitive costs. While certain technologies, such as fluorescent, showed strengths at higher flux levels, LED offered the best overall performance across both indoor and outdoor lighting.

Data availability statement

All relevant data are within the article and its Supporting Information files.

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Appendix

Table 3. Values of eight technology alternatives per criterion.

Lighting detail*	Luminous-flux (lumens)	Capital costs ($)	Life-cycle Costs ($)	Energy consumption (kWh)	kg CO_2e	kg NO_x	kg SO_2	kg $PM_{2.5}$
Light emitting diode (LED)	5000	46.74	252.46	4311.02	1626.6	0.92	0.8	0.2
	7500	62.32	378.7	6466.54	2439.9	1.37	1.19	0.3
	10 000	77.9	504.93	8622.05	3253.21	1.83	1.59	0.4
	12 500	93.47	631.16	10 777.56	4066.51	2.29	1.99	0.5
	15 000	124.63	757.39	12 933.07	4879.81	2.75	2.39	0.6
Fluorescent (LFL)	5000	70.88	570.01	9733.33	3672.51	2.07	1.8	0.45
	7500	94.51	855.01	14 600	5508.76	3.1	2.7	0.68
	10 000	118.14	1140.01	19 466.67	7345.02	4.13	3.59	0.9
	12 500	141.76	1425.02	24 333.33	9181.27	5.17	4.49	1.13
	15 000	165.39	1710.02	29 200	11 017.52	6.2	5.39	1.35
High pressure sodium	5000	63.13	356.25	6083.33	2295.32	1.29	1.12	0.28
	7500	126.26	534.38	9125	3442.98	1.94	1.68	0.42
	10 000	126.26	712.51	12 166.67	4590.64	2.58	2.25	0.56
	12 500	126.26	890.64	15 208.33	5738.29	3.23	2.81	0.7
	15 000	189.39	1068.76	18 250	6885.95	3.87	3.37	0.84
Low pressure sodium (LPS)	5000	400.86	178.13	3041.67	1147.66	0.65	0.56	0.14
	7500	400.86	267.19	4562.5	1721.49	0.97	0.84	0.21
	10 000	801.72	356.25	6083.33	2295.32	1.29	1.12	0.28
	12 500	801.72	445.32	7604.17	2869.15	1.61	1.4	0.35
	15 000	801.72	534.38	9125	3442.98	1.94	1.68	0.42
Induction lighting	5000	215.54	183.22	3128.57	1180.45	0.66	0.58	0.14
	7500	215.54	274.82	4692.86	1770.67	1	0.87	0.22
	10 000	323.31	366.43	6257.14	2360.9	1.33	1.16	0.29
	12 500	431.09	458.04	7821.43	2951.12	1.66	1.44	0.36
	15 000	431.09	549.65	9385.71	3541.35	1.99	1.73	0.43
Metal halide lighting	5000	141.42	400.79	6843.75	2582.23	1.45	1.26	0.32
	7500	141.42	601.18	10 265.63	3873.35	2.18	1.9	0.47
	10 000	141.42	801.57	13 687.5	5164.46	2.91	2.53	0.63
	12 500	282.83	1001.97	17 109.38	6455.58	3.63	3.16	0.79
	15 000	282.83	1202.36	20 531.25	7746.7	4.36	3.79	0.95
Standard incandescent	5000	1523.94	3206.29	54 750	20 657.86	11.62	10.11	2.53
	7500	1523.94	4809.43	82 125	30 986.79	17.43	15.16	3.8
	10 000	2285.91	6412.58	109 500	41 315.72	23.24	20.22	5.06
	12 500	3047.87	8015.72	136 875	51 644.65	29.06	25.27	6.33
	15 000	3047.87	9618.87	164 250	61 973	34.87	30.32	7.6
Halogen	5000	644.15	1781.27	30 416.67	11 476.59	6.46	5.62	1.41
	7500	966.23	2671.91	45 625	17 214.88	9.69	8.42	2.11
	10 000	1288.31	3562.54	60 833.33	22 953.18	12.91	11.23	2.81
	12 500	1610.38	4453.18	76 041.67	28 691.47	16.14	14.04	3.52
	15 000	1932.46	5343.81	91 250	34 429.76	19.37	16.85	4.22

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